

GEFÖRDERT VOM



Bundesministerium  
für Bildung  
und Forschung



Finanziert von der  
Europäischen Union  
NextGenerationEU



German  
Research Center  
for Artificial  
Intelligence

# AnoMed-Seminar

## Towards Privacy and Utility in Tourette Tic Detection Through Pretraining Based on Publicly Available Video Data of Healthy Subjects

**Nele Sophie Brügge**, Esfandiar Mohammadi, Alexander Münchau,  
Tobias Bäumer, Christian Frings, Christian Beste, Veit Roessner, Heinz Handels

 UNIVERSITÄT  
TRIER

 TECHNISCHE  
UNIVERSITÄT  
DRESDEN

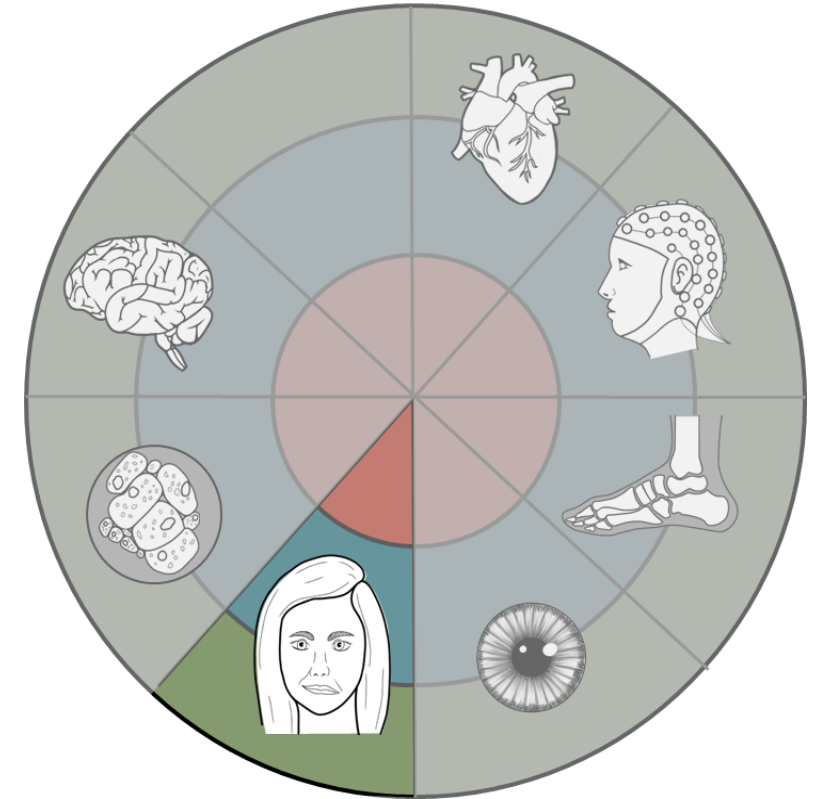


UNIVERSITÄT ZU LÜBECK



# Medical Video Analysis in AnoMed

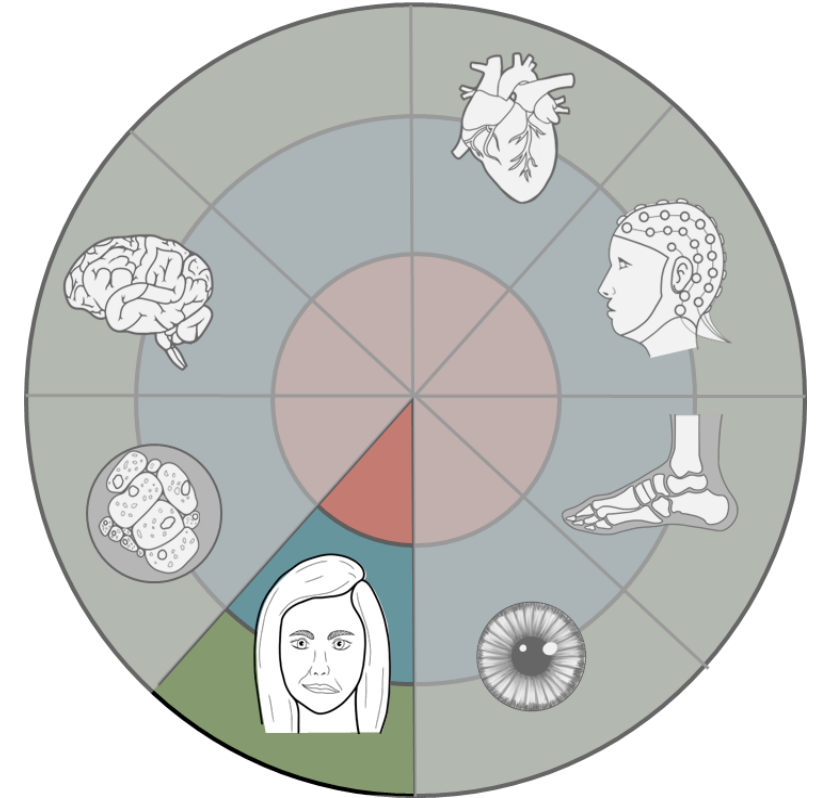
- Example dataset: **Toronto NeuroFace [1]**
  - Publicly available dataset
  - **Videos of oro-facial gestures performed by subjects with oro-facial impairment due to neurological disorders** with amyotrophic lateral sclerosis (ALS) and stroke.
  - Annotations: Clinical scores, facial landmarks



[1] Bandini, Andrea et al. "A New Dataset for Facial Motion Analysis in Individuals With Neurological Disorders." *IEEE journal of biomedical and health informatics* vol. 25,4 (2021): 1111-1119. doi:10.1109/JBHI.2020.3019242

# Medical Video Analysis in AnoMed

- Example dataset: **Toronto NeuroFace [1]**
    - Publicly available dataset
    - **Videos of oro-facial gestures performed by subjects with oro-facial impairment due to neurological disorders** with amyotrophic lateral sclerosis (ALS) and stroke.
    - Annotations: Clinical scores, facial landmarks
- ➔ Why should medical videos be analyzed with machine learning?

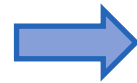
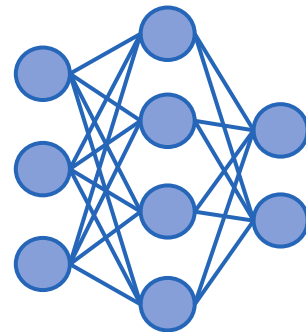
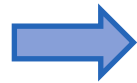


[1] Bandini, Andrea et al. "A New Dataset for Facial Motion Analysis in Individuals With Neurological Disorders." *IEEE journal of biomedical and health informatics* vol. 25,4 (2021): 1111-1119. doi:10.1109/JBHI.2020.3019242

# Medical Video Analysis

## Examples:

- **Gait analysis**, e.g. when using prostheses, after injuries or accidents
- **Neurological and motor disorders** (Developmental coordination disorders, stereotypic movement disorders, tic disorders)
- **Mental diseases**



Therapeutic monitoring

Diagnostic support

Treatment planning

Disease understanding

[1] Photo: from P. Barros, N. Churamani, E. Lakomkin, H. Siqueira, A. Sutherland, and S. Wermter, "The OMG-Emotion Behavior Dataset," in 2018 International Joint Conference on Neural Networks (IJCNN), Pages: 7, Rio de Janeiro, Brazil: IEEE, Jul. 2018, pp. 1408–1414.

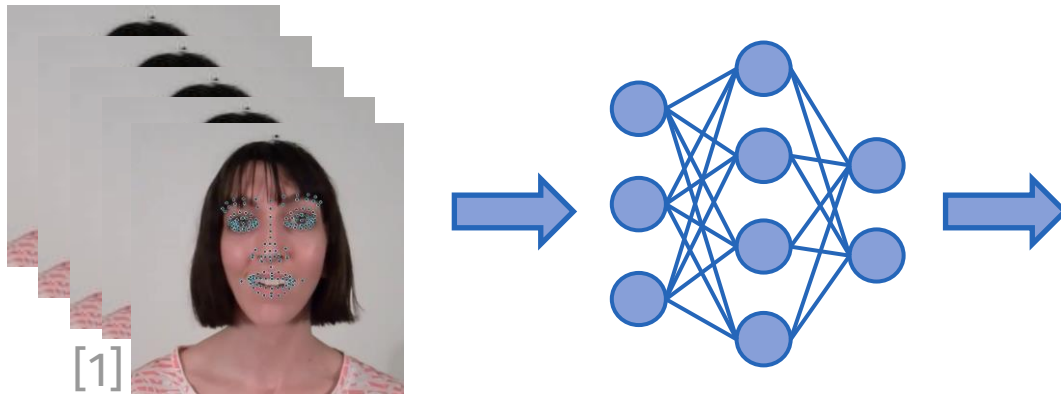
# Motivation – Tic Detection

## Gilles de la Tourette Syndrome

- Neurodevelopmental disorder
- Prevalence: 0.3 – 0.9 %

## Prior work

- Limited applicability: Additional sensors, subject-specific, healthy subjects
- No consideration of data privacy



Therapeutic monitoring

Diagnostic support

Treatment planning

Disease understanding

Assessment of tic  
severity and  
frequency

[1] Photo: from P. Barros, N. Churamani, E. Lakomkin, H. Siqueira, A. Sutherland, and S. Wermter, "The OMG-Emotion Behavior Dataset," in 2018 International Joint Conference on Neural Networks (IJCNN), Pages: 7, Rio de Janeiro, Brazil: IEEE, Jul. 2018, pp. 1408–1414.

# Privacy-Preserving Machine-Learning

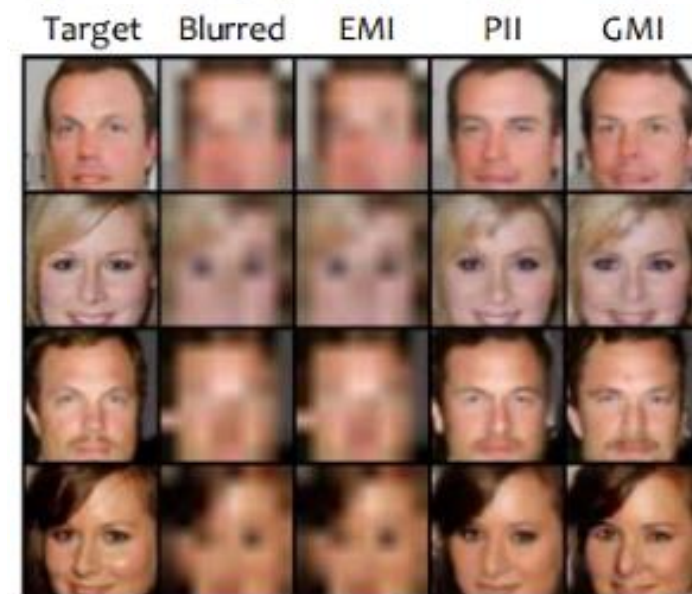
**Ideally:** Encode **general patterns** rather than facts about specific training examples  
**By default:** Machine learning models do not learn to ignore these specifics

## Attack examples:

- Reconstruction attack [3]
- Membership inference attack [4]

## Challenges in Medical Video Analysis:

- High-dimensional input data
- Small datasets
- Rare diseases and special cases



[2]

[3] Zhang, Yuheng et al. "The Secret Revealer: Generative Model-Inversion Attacks Against Deep Neural Networks." IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 250-258.  
[4] R. Shokri, M. Stronati, C. Song and V. Shmatikov, "Membership Inference Attacks Against Machine Learning Models," 2017 IEEE Symposium on Security and Privacy (SP), San Jose, CA, USA, 2017, pp. 3-18.

# Privacy-Preserving Machine-Learning

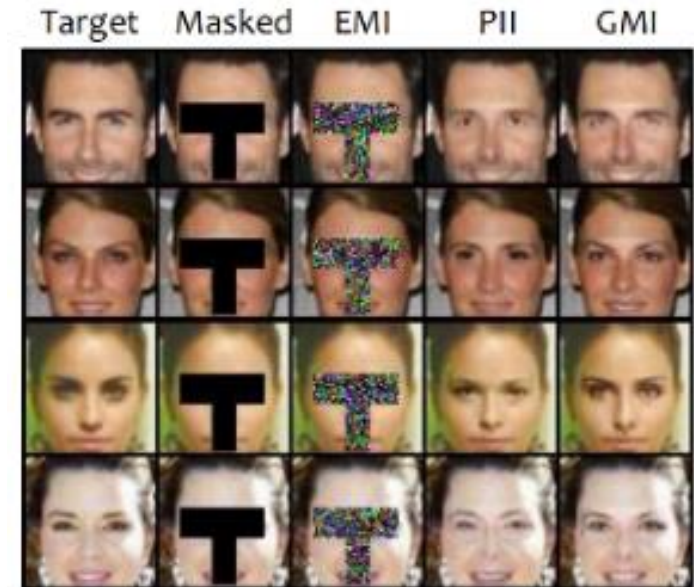
**Ideally:** Encode **general patterns** rather than facts about specific training examples  
**By default:** Machine learning models do not learn to ignore these specifics

## Attack examples:

- Reconstruction attack [3]
- Membership inference attack [4]

## Challenges in Medical Video Analysis:

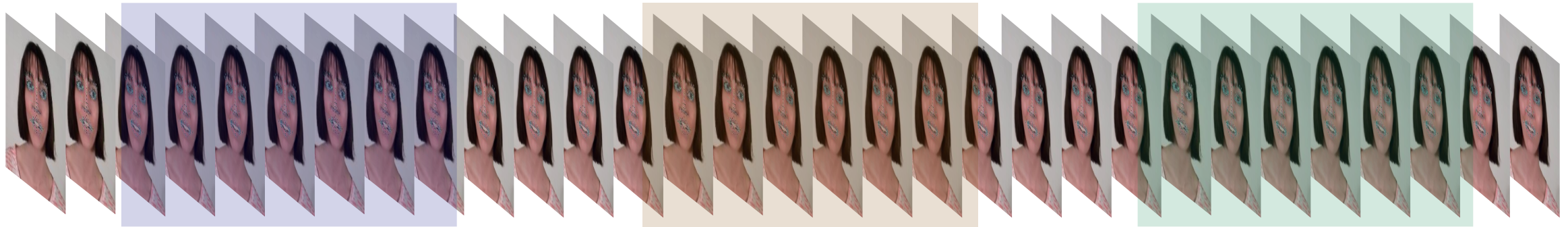
- High-dimensional input data
- Small datasets
- Rare diseases and special cases



[2]

[3] Zhang, Yuheng et al. "The Secret Revealer: Generative Model-Inversion Attacks Against Deep Neural Networks." IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 250-258.  
[4] R. Shokri, M. Stronati, C. Song and V. Shmatikov, "Membership Inference Attacks Against Machine Learning Models," 2017 IEEE Symposium on Security and Privacy (SP), San Jose, CA, USA, 2017, pp. 3-18.

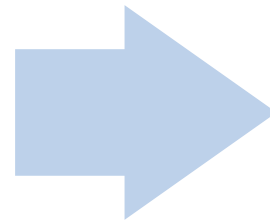
# Amplifying Membership Inference Attacks



**Amplification of snippet-based attacks**  
using Chernoff-Hoeffding bound

$$\Pr \left[ \frac{1}{n} \sum X_i > p + \delta \right] \leq \exp \left( -\frac{\delta^2 n}{2p(1-p)} \right) [1, 2]$$

$n$ : Number of random variables  
 $X_i$ : Random variables in  $\{0,1\}$   
 $p$ : Expectation value of  $X_i$   
 $\delta$ : Deviation from expected result

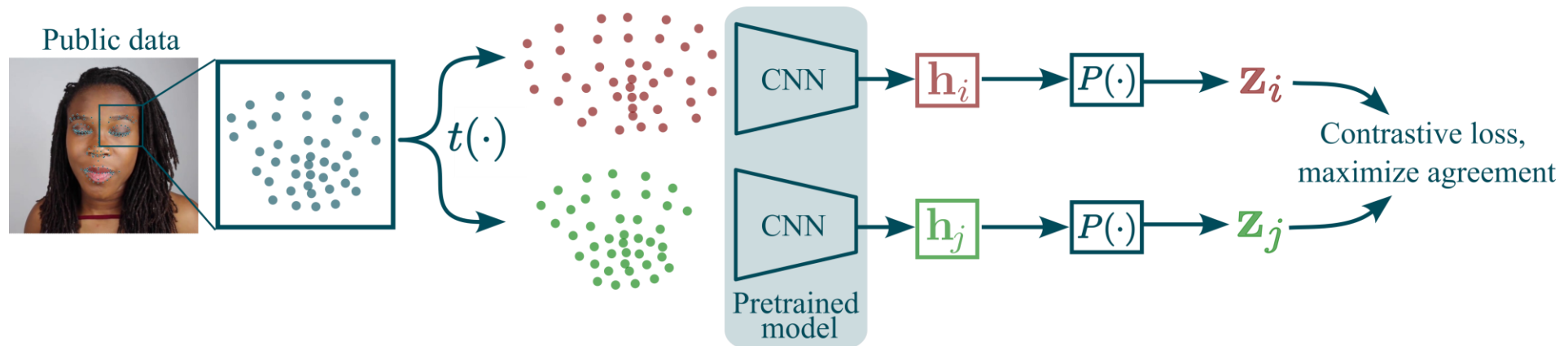


With  $p = 0.5$ : calculating an  
**upper bound how much the**  
MIA result **deviates from that**  
**of a random classifier**



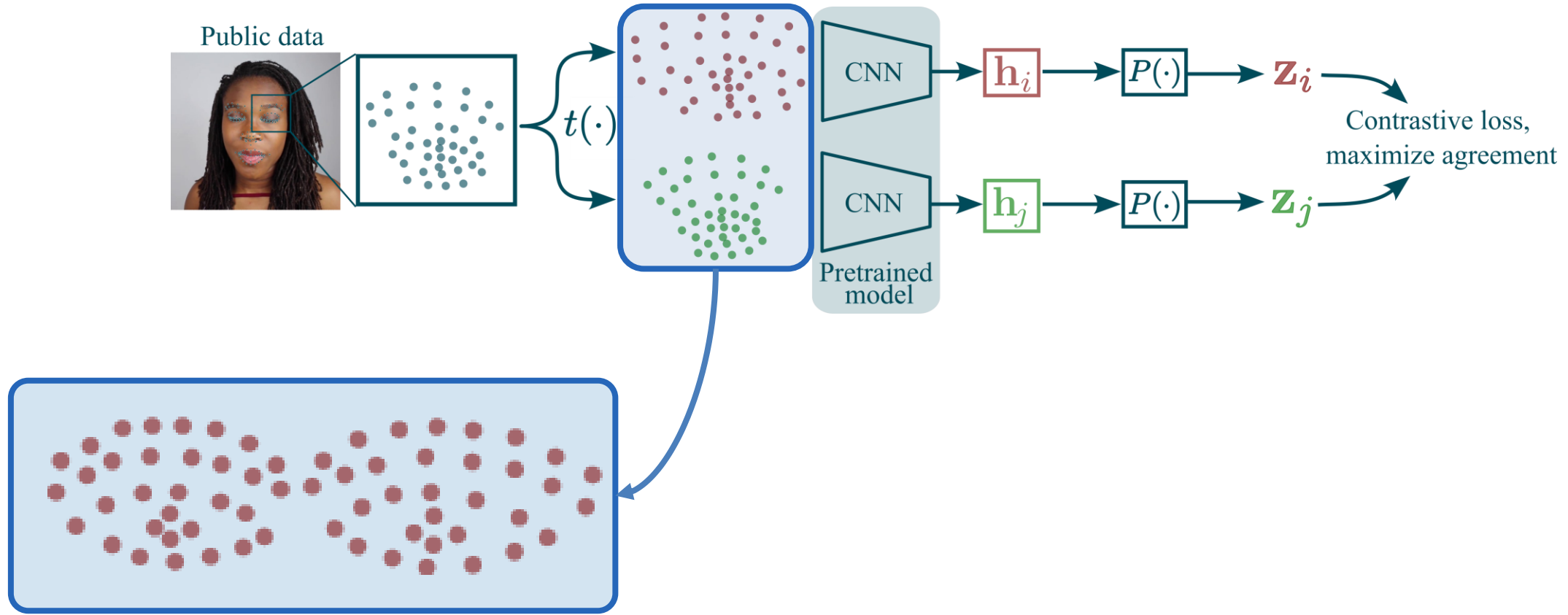
# Proposed Two-Stage Neural Network

## Stage 1: Contrastive Learning with landmarks



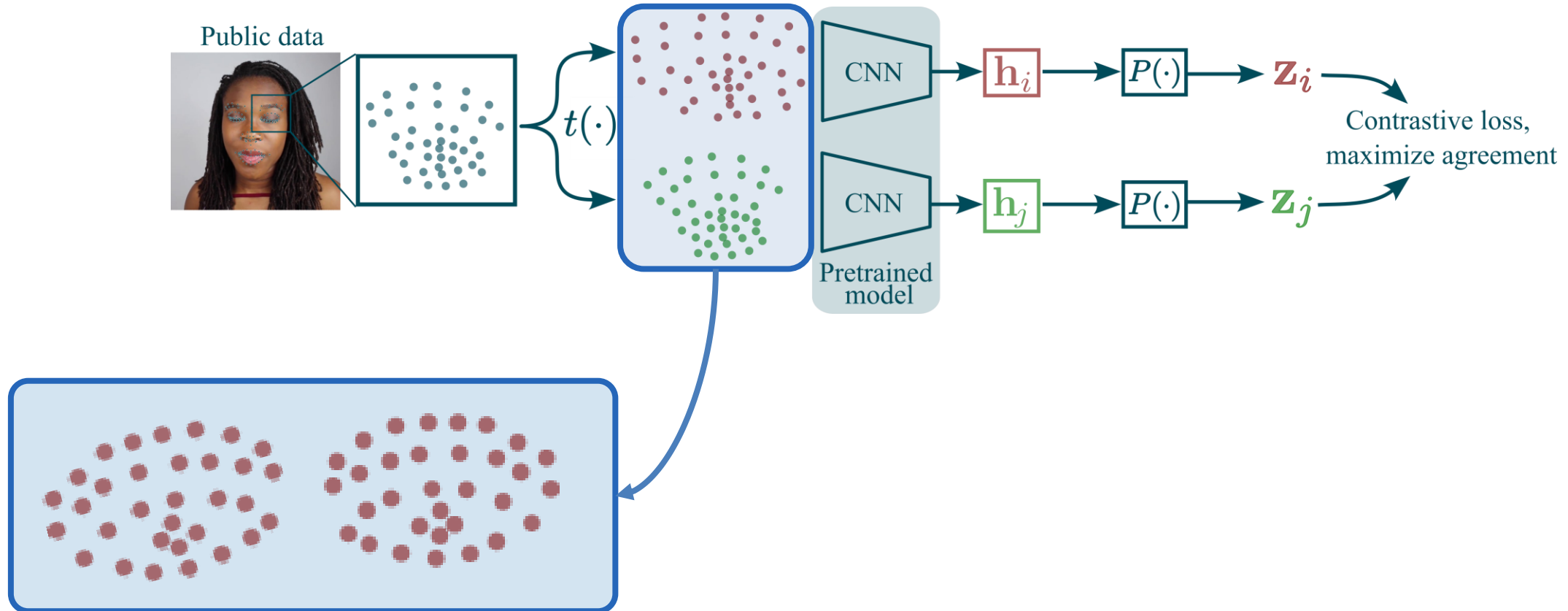
# Proposed Two-Stage Neural Network

## Stage 1: Contrastive Learning with landmarks



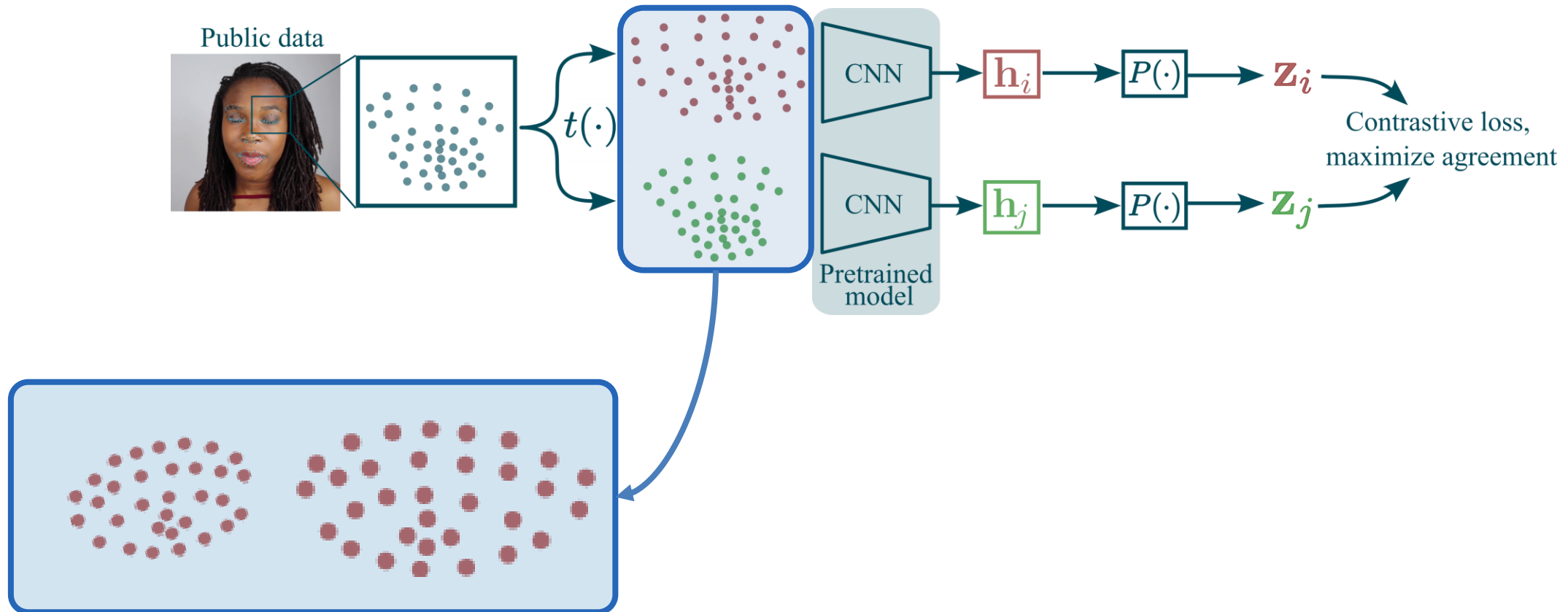
# Proposed Two-Stage Neural Network

## Stage 1: Contrastive Learning with landmarks



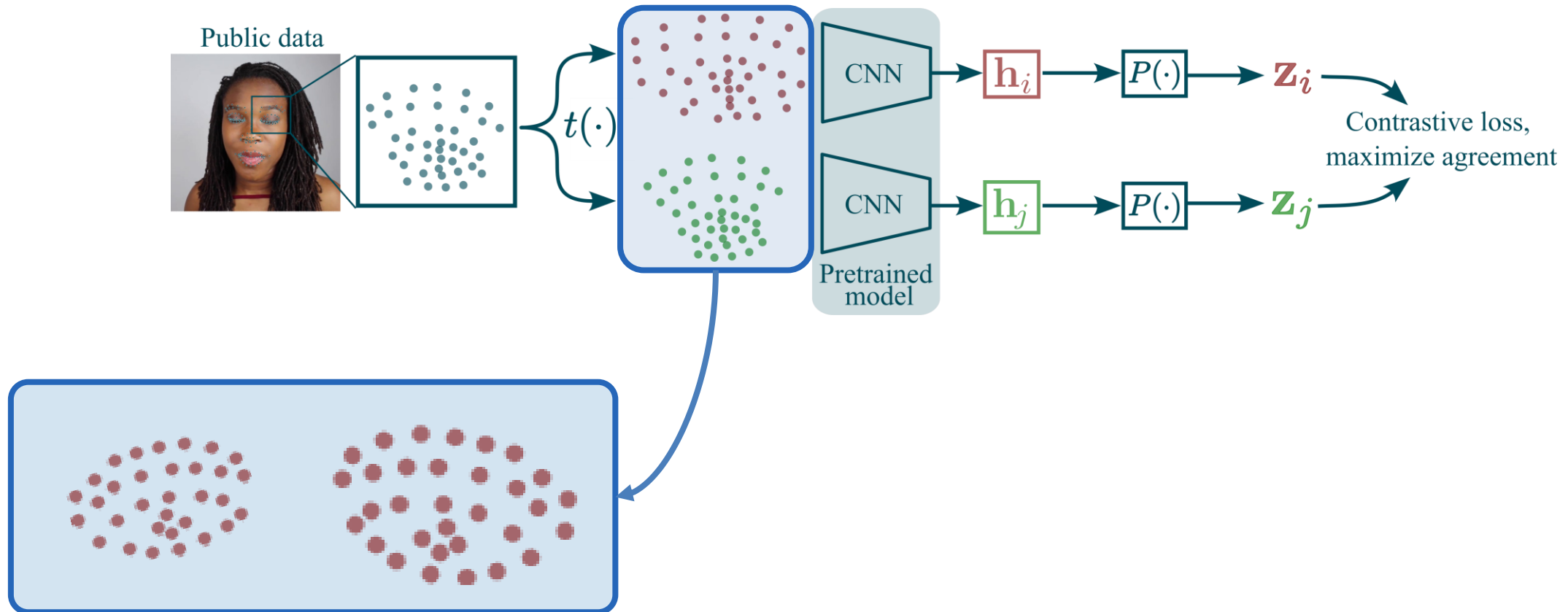
# Proposed Two-Stage Neural Network

## Stage 1: Contrastive Learning with landmarks



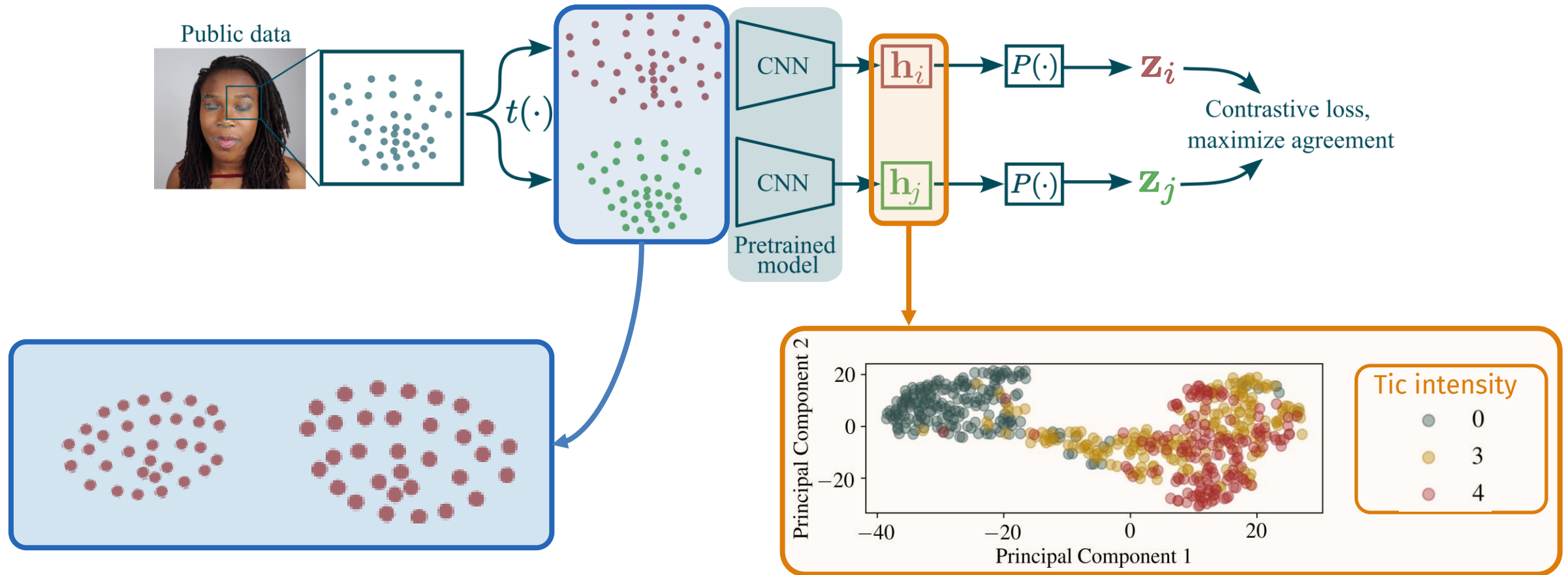
# Proposed Two-Stage Neural Network

## Stage 1: Contrastive Learning with landmarks



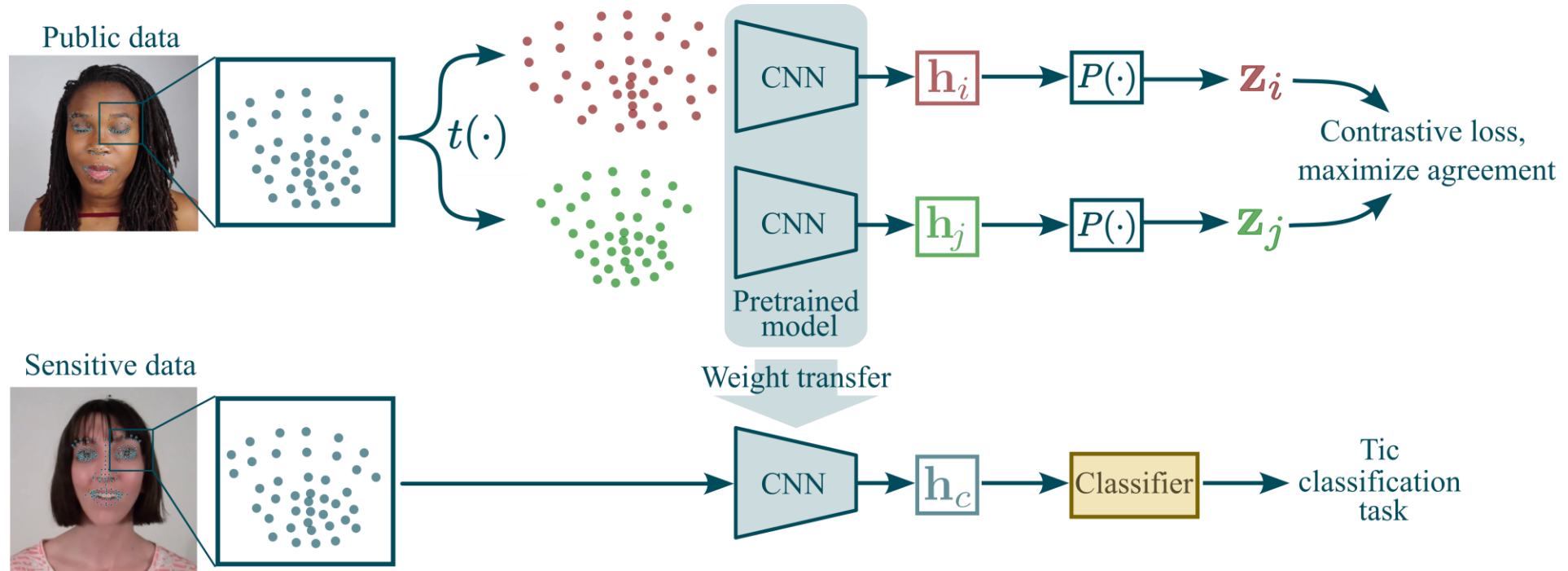
# Proposed Two-Stage Neural Network

## Stage 1: Contrastive Learning with landmarks



# Proposed Two-Stage Neural Network

## Stage 2: Training a classifier based on Contrastive Learning features



# Tic Detection and Attack Results

Method	MIA Accuracy	Amplified MIA $P[random]$	Tic Detection Accuracy
Fully-Supervised CNN	73.10	4.07	81.92
Fully-supervised CNN + augment	65.65	23.00	85.76
Pretraining + Classifier	52.15	97.26	86.53
DP-Training of Classifier ( $\epsilon=1$ )	50.14	99.80	80.09

(Amplified) membership inference attack (MIA) and tic detection accuracy for three different deep learning approaches.

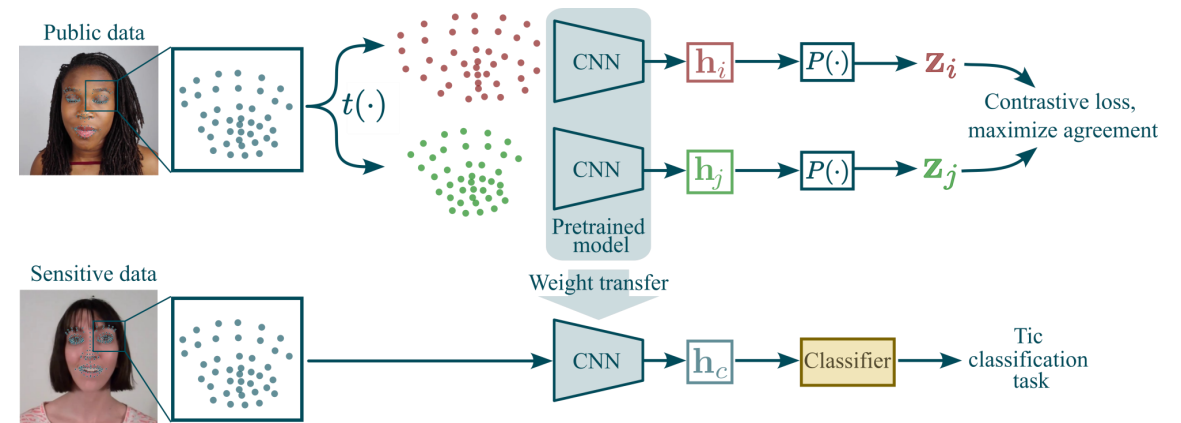


Most important landmarks determined via SHAP analysis



# Conclusion

- Supervised training on **small medical datasets**  
→ **models leak information** about training data
- **Amplification of membership attacks** if multiple inputs per subjects are used
- **Two-stage learning approach leveraging data of healthy subjects**
  - Contrastive learning on landmarks
  - Effectively defends against MIAs
  - Reaches the highest classification accuracy of 86.5 %
  - Useful for various medical-related problems

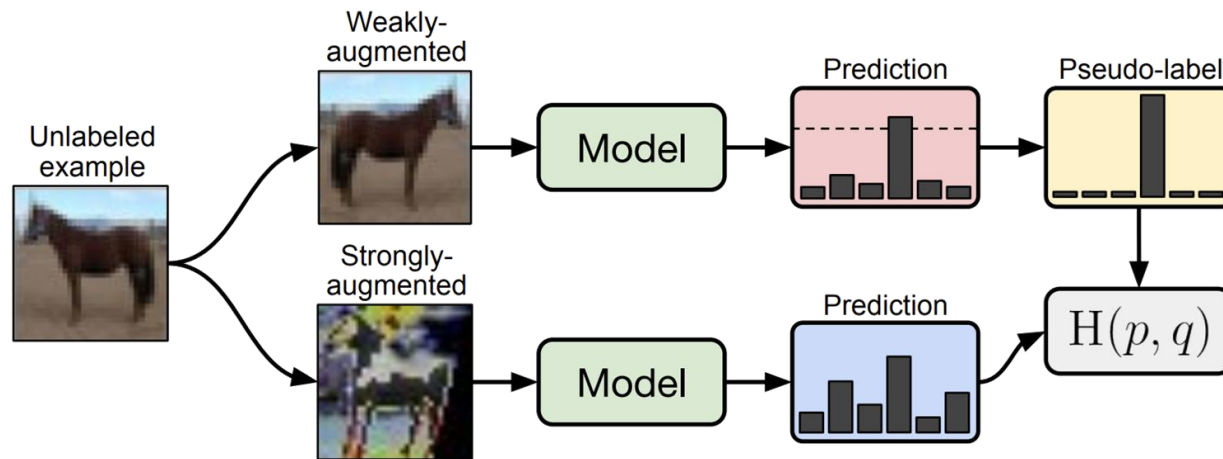


# Past, Ongoing and Future Work

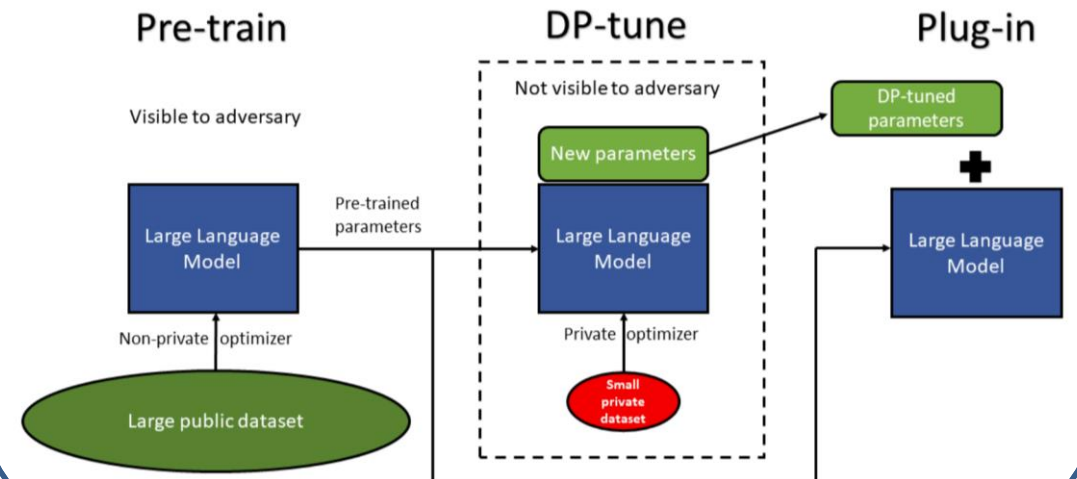
## Next steps:

- Provide provable privacy guarantees + and good utility also for small datasets
- Prepare AnoMed privacy challenge for video data

### Semi-Supervised Training



### Differentially-private finetuning of large deep learning models

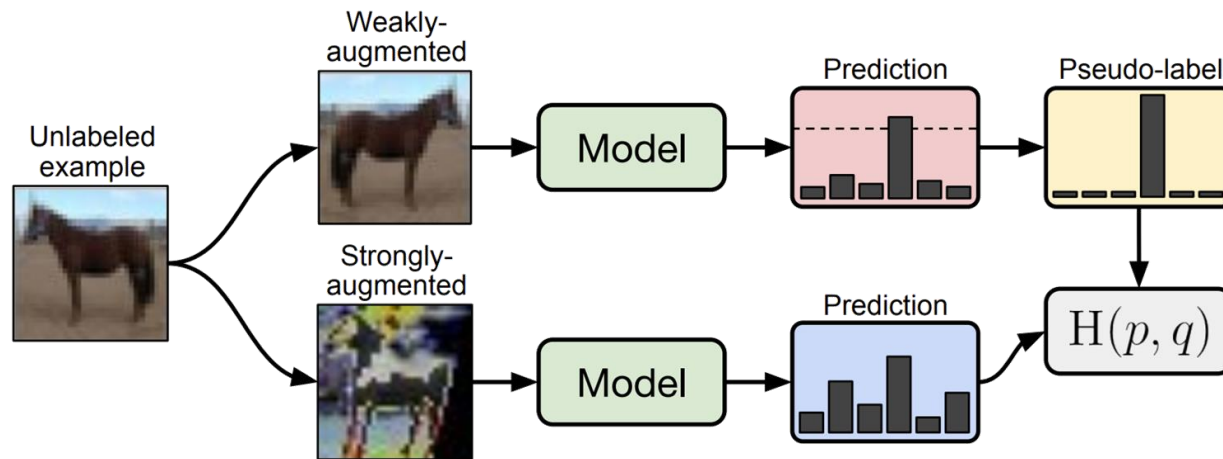


# Past, Ongoing and Future Work

## Next steps:

- Provide provable privacy guarantees + and good utility also for small datasets
- Prepare AnoMed privacy challenge for video data

## Semi-Supervised Training



## Differentially-private finetuning of large deep learning models

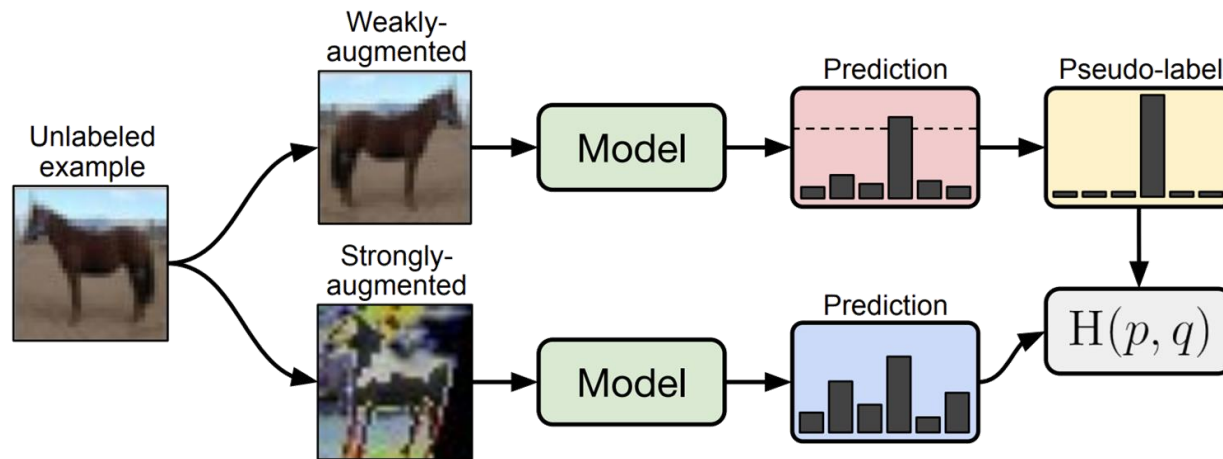
- Finetuning only the parameters that change the most during a gradient update
- Find the most efficient network update to save privacy budget
- Find collisions of two data points of different classes the in the neural network and finetune only this region
- **Finetune a low-rank approximation of the original network weights**

# Past, Ongoing and Future Work

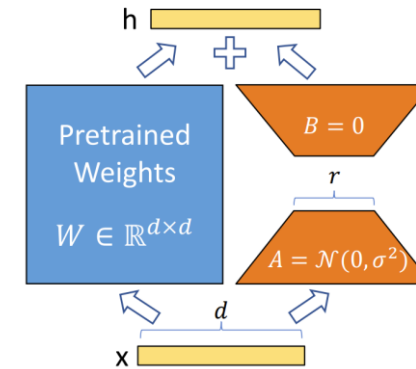
## Next steps:

- Provide provable privacy guarantees + and good utility also for small datasets
- Prepare AnoMed privacy challenge for video data

## Semi-Supervised Training



## Differentially-private finetuning of large deep learning models



- **Finetune a low-rank approximation of the original network weights**

# Contact



Nele Sophie Brügge

Researcher

DFKI Branch Office Lübeck

Artificial Intelligence in Medical Image Processing

Ratzeburger Allee 160

23562 Lübeck

 [nele.bruegge@dfki.de](mailto:nele.bruegge@dfki.de)

